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Analysing Carbon Pass-Through Rate Mechanism in the Electricity Sector: Evidence from Greece

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Abstract

In this study, we shed light into the carbon pass-through rate mechanism to wholesale prices in the Greek electric market. For this reason, we utilize a rich micro-level panel, including hourly data for 23 power plants spanning the period January 2014 to December 2017. In order to study the pass-through of emissions costs to wholesale electricity prices, we used an instrumental variable methodology. Our findings survived several robustness checks, accounting for logged linear and non-linear econometric specifications. Moreover, they are in alignment with the relevant recent literature, indicating the existence of an almost complete pass-through rate mechanism. This means that electricity firms almost fully internalize the cost of CO_2 permits, incurring important policy implications to policy makers and government officials.

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Keywords: Emissions; CO_2 permits; Pass-through; Instrumental variable; Electricity industry
JEL codes: L13; L94; Q52.

1. Introduction

The cost pass-through mechanism, namely the change in prices resulting from an input cost shock, has been puzzled economists and policy makers during the last twenty years. The topic has increasingly become important to economists in a number of fields including Industrial Organization, Macroeconomics and Public Finance, which, helped spawn a large theoretical and empirical literature (see for example Goldberg and Knetter, 1997; Nakamura, 2008; Verboven and van Dijk, 2009; Gopinath et al, 2010; Nakamura and Zerom, 2010; Aguirre et al., 2010; Marion and Muehlegger, 2011; Richards et al, 2012; Jaffe and Weyl, 2013; Weyl and Fabinger, 2013; Goldberg and Hellerstein, 2013; Fabra and Reguant, 2014).

Most of these studies consent that the exchange rate pass-through is incomplete ranging about 50-60% (Goldberg and Knetter, 1997; Hellerstein, 2008, Nakamura, 2008; Nakamura and Zerom, 2010; Duso and Szücs, 2017). One possible explanation for such asymmetric pass-through is that firms adjust their markups to accommodate the local market environment (see for example Krugman, 1986; Helpman and Krugman, 1987). The study of Feenstra, (1989), sheds some light on the explanation of the incomplete pass-through by linking the latter to the presence of imperfect competition. This study uses a log-linear model and quarterly data over the period 1974:1 to 1987:1 for the U.S. imports of Japanese cars, compact trucks and heavy motorcycles to find that there is a symmetric response of import prices to changes in the bilateral exchange rate and an import tariff.

Moreover, recent theoretical contributions have suggested a number of potentially important factors explaining the existence of an incomplete exchange rate pass-through, including *inter alia* the existence of local costs and the importance of significant barriers that hinder price adjustment mechanism (i.e menu costs). In an influential study, Nakamura and Zerom (2010), study a structural oligopoly model that nests three potential factors (i.e markup adjustment, local costs, menu costs) in order to estimate and decompose the degree of price pass-through in a commodity market (coffee industry at the wholesale and retail market segment). The empirical findings suggest an incomplete pass-through elasticity of coffee prices of 25%. In a similar study, Goldberg and Hellerstein (2013) argue that only 5% of an exchange rate change is transmitted to final beer prices. In an interesting study, Bonnet et al, (2013), use a structural oligopoly framework to assess the role of vertical restraints (i.e nonlinear pricing contracts, resale price maintenance-RPM) in affecting the price pass-through to input cost shocks. They argue that vertical restraints such as RPM increase the degree of the pass-through rate compared to linear pricing.

It is worth emphasizing that the incomplete pass-through rate mechanism can be attributed into four main reasons: a) Mark-up adjustment as a result of an input cost shock, b) The existence of non-traded costs that remain unaffected by the observed cost shocks (see Goldberg and Hellerstein, 2008), c) The presence of nominal price rigidities due to the characteristics of the industry (e.g scale economies, barriers to entry, market concentration, etc) that hinder the exact price adjustment mechanism to responses to cost shocks (Nakamura and Zerom, 2010; Goldberg and Hellerstein, 2013) and finally d) The mismatch between observed cost shocks and firms' actual or opportunity costs (Fabra and Reguant, 2014).

Contrary to the existing literature on pass-through rate mechanism, a recent study (see Fabra and Reguant, 2014) argues that the average pass-through in the wholesale Spanish electricity market segment is almost complete (above 80%). It is also highlighted that firms in the electricity industry are more able to pass-through costs in peak hours rather than the low-demand hours (off-peak) with the relevant estimate of the pass-through rate to reach almost 100%. This means that a one euro increase in the price of carbon permits (e.g emissions costs) leads, on average, into a one euro increase in the level of wholesale electricity prices (i.e system marginal price). The almost-complete pass-through mechanism might be attributed to certain characteristics of the electricity industry (i.e high-frequency auctions, highly inelastic demand, etc). These structural elements, justify that electricity firms have weak incentives to adjust markups after a cost shock. Moreover, this study argues that the costs of price adjustment are relatively small, mitigating the rigidity of pass-through rate mechanism. On the contrary, in an earlier study, about price pass-through in the wholesale electricity industry in Germany, Zachmann and Von Hirschhausen (2008) claim that cost pass-through between EU emissions allowances and electricity future prices is incomplete and asymmetric. In other words, they argue that positive (negative) cost shocks are transmitted more (less) strongly to the electricity retail prices. In a more recent study, Duso and Szücs, (2017), investigate how the wholesale electricity prices are transmitted to retail tariffs in Germany over the 2007–2014 period. Similarly to the majority of the price pass-through literature, they find that the average pass-through is incomplete at around 60%, exhibiting however a large degree of heterogeneity between competitive and non-competitive segments of the market.

Although there is a growing interest by policy makers and practitioners on the impact of supply and demand shocks on energy markets (Barsky and Kilian, 2002; Hamilton, 2003; Kilian 2008a, Kilian 2008b; Kilian, 2009a; Kilian, 2009b; Apergis and Polemis, 2018 among others) little attention has been paid on the examination of the microeconomic consequences of cost pass-through rate mechanism in a highly volatile commodity industry such as electricity. This study aims to fill this gap in the literature by estimating the degree of carbon cost pass-through (i.e complete, incomplete) in the electricity industry. The main reason for focusing solely on the wholesale rather than the retail electricity industry in Greece stems from the fact that electricity retail prices although deregulated, are not fully responsive to wholesale prices and therefore invariant, at least in the short-run, to changes in the production costs (IEA, 2018; Fabra and Reguant, 2014). The empirical findings indicate the existence of an almost complete pass-through rate mechanism prevailing in the Greek wholesale electricity market segment.

This study contributes in many fronts. First and foremost, it is the first study that estimates the degree of the pass-through rate mechanism in a highly volatile commodity market. Given that the Greek electricity industry is comprised of competitive (i.e generation and supply of electricity) and regulated (e.g power transmission and distribution) market segments, carbon pass-through constitutes a substantially important cost element both for the firm and the regulator. In this sense, we attempt to shed light on the mechanism of input cost shocks and how these shocks have changed over time or under different demand characteristics. Second, it goes beyond the existing literature in that it uses a particularly long and updated panel of 23 power plants on an intra-day basis over the period January 2014-December 2017. The reason for limiting our sample to this specific time span, stems from the fact that the sample period concerns a period with the same regulatory framework on wholesale price formation as well as a period belonging in the third and more mature phase (2013-2020) of the European cap-and-trade program for carbon, known as the European Union's Emissions Trading System (ETS). Under this regime, European Emission Allowances (EUA) are traded in the liquid European Energy Exchange (EEX) platform. Moreover, this capacity mix in this period has been almost stable, as the rapid evolution of renewables lasted up to year 2013, while commissioning of new thermal units did not take place. Lastly, our empirical findings raises some important implications to policy makers and government officials.

The rest of this paper proceeds as follows. Section 2 offers a detailed description of the Greek electricity industry. Section 3 presents the theoretical framework prevailing under different demand functions in order to explain the pass-through rate mechanism. Section 4 describes the context and data of the analysis along with the empirical modelling. In Section 5, we present the findings of the empirical analysis and the necessary robustness cheeks. Finally, Section 6 concludes the paper.

2. The Greek electricity industry

The Greek wholesale electricity industry has not yet implemented the European "*target model*", namely the establishment of a forward, day-ahead, intra-day and balancing market, enabling also the existence of bilateral contracts among producers and final consumers of demand aggregators. It still runs as a mandatory pool, where all producers, traders and retailers are obliged to participate in the wholesale market, consisting of a day-ahead market, co-optimizing energy and ancillary services, and an imbalance market, clearing deviations among schedule and actual volumes. In other words, each power plant participates in the wholesale market through the submission of energy supply offer, supplemented by techno-economic declarations that incorporates technical and economic characteristics of each unit.

Figure 1 portrays the energy supply offer for a thermal unit, compared to its differential cost and its minimum variable cost, for different power outputs, among unit's technical minimum (P_{min}) and technical maximum (P_{max}). The relevant figure also shows that each power unit can submit an energy supply offer (red curve) for its whole capacity in up to ten steps, considering that they lower from a regulated upper value (CAP variable) and higher than the minimum average variable cost (green curve) of each power unit. The latter curve derives from the submitted techno-economic characteristics that create the differential cost curve (black curve) and allows the estimation of the minimum average variable cost curve, which has a flat value.

<Insert Figure 1 about here>

As it is evident all the relevant curves have a stepwise and not linear form. Specifically, the steps of the energy supply offer are not symmetrical, as usually the first step concerns the technical minimum of a power unit, where unit aims to guarantee a realistic technical scheduling, while the rest steps concern the strategy adopted by each power producer. The bidding strategy is formulated considering the regulatory constraint of not allowing bidding lower from the Minimum Average

Variable Cost (MAVC) of each power plant. Moreover, this strategy depends on the portfolio of each producer, the competitiveness of each power unit, the share of vertical utilities in retail market compared to the share in electroproduction in the wholesale market. Independent Power Producers (IPPs) usually adopt a scarcity pricing approach to maximize their revenues from their electroproduction assets, while Public Power Corporation (PPC) usually adopts a minimum variable cost strategy, as it aims at lower system marginal prices (SMP) in the wholesale market.

Figure 1 also presents the regulatory provision, known as the "*30% rule*", which allows a deviation from bidding below the MAVC. We have to mention though that the latter regulatory mechanism, which was abolished by the regulator in 1/1/2014, thermal units were allowed to submit their first step (red line with number 1), which was set at 30% of their technical maximum capacity, at a cost lower than their MAVC (green line). Practically, all units submitted a zero price for this step, which practically led thermal units to operate at their technical minimum. However, the rule was considered as a distortion in the market, as it did not depict the actual system marginal price, leading to its abolishment with decision 338/2013 of the Regulatory Authority of Energy (RAE). This reason has led us to select the period 2014-2017 as the examined period, so as to have the same regulatory environment for the wholesale price formation.

In the Greek electricity industry, there are 24 thermal power plants subject to emissions control, 14 of which are lignite plants, 9 are new combined cycle gas plants, and one is traditional oil and gas plant (see Table 1). The emissions rate of each plant depends, not only on the energy content of each fuel, but also on the operating level of the power plant, as operation close to the nominal capacity has a lower emissions rate than operation in the technical minimum. The average emissions rate of lignite plants is about 1.5 tons/MWh. It is worth mentioning that combined cycle natural gas units (CCGTs) have much lower emissions rates, averaging about 0.4 tons/MWh with little dispersion across plants. Since lignite plants typically have lower marginal costs than CCGTs over the examined period with relatively low CO_2 prices on average (70% versus 40% over the sample), they operate closer to their full potential (Fabra and Reguant, 2014). Finally, traditional oil fired or gas fired plants that are more inefficient than newer gas plants, only operating at almost 0% of their capacity on average. During the sample period, the Greek wholesale electricity industry is dominated by one vertically integrated firm (PPC), plus a small number of IPPs. In 2016, PPC, accounted for 79% of the installed thermal generation capacity and for about 75% of thermal electricity generation. It is noteworthy that PPC's share in the day-ahead market was approximately 53%, while its share to the retail market segment was about 88% in 2016 (IEA, 2018).

<Insert Table 1 about here>

3. Theoretical framework

In this section, we build the structural conceptual model used to estimate the pass-through rate of emissions costs to wholesale electricity prices in Greece. Let the inverse demand function p(q) given by the following equation:

$$p(q) = \frac{a}{b} - \frac{1}{b} q \tag{1}$$

Let's assume that the marginal cost c is fixed. In this industry, profit maximization requires the fulfillment of first (FOC) and second (SOC) order conditions, namely:

$$p + qp' = c \tag{2}$$

$$2p' + qp'' < 0 \tag{3}$$

where $c \geq 0$ and $\rho < 2$

Alternatively, using the elasticity of demand e_d and convexity conditions, we have:

$$e_d \equiv -\frac{p(q)}{qp'(q)} \tag{4}$$

$$\rho \equiv -\frac{qp''(q)}{p'(q)} \tag{5}$$

Where ρ denotes the curvature/convexity demand parameter. Combining equations 4 and 5 we have:

$$\frac{p}{c} = \frac{e_d}{e_d - 1} \tag{6}$$

The magnitude of the pass-through rate can be calculated simply by taking the first derivative of price compared to cost $\left(\frac{dp}{dc}\right)$. According to the FOC, we have:

$$p + qp' = c \Rightarrow \frac{\partial p}{\partial c} = \frac{1}{2-\rho} \tag{7}$$

In such a case, the threshold for complete (100%) pass-through or more is given as:

$$\frac{\partial p}{\partial c} - 1 = \frac{\rho - 1}{2-\rho} \geq 0 \tag{8}$$

However, it is widely acknowledged by the theoretical literature (see for example Bulow and Pfleiderer, 1983; Weyl-Fabinger, 2013; Gopinath et al, 2010; Mrazova et al, 2015) that demand functions implying constant pass-through take the following form:

$$p(q) = a + \beta q^{\frac{1-a}{a}} \tag{9}$$

The constant pass-through rate in this case is given as:

$$\frac{\partial p}{\partial c} = a \tag{10}$$

When we use the elasticity of demand formulation, Equation (7) becomes:

$$\frac{\partial \log p}{\partial \log c} = \frac{\varepsilon_d - 1}{e_d} \times \frac{1}{2-\rho} \tag{11}$$

So threshold for full (100%) or more pass-through takes the following form:

$$\frac{\partial \log p}{\partial \log c} - 1 = \frac{e_d \rho - e_d - 1}{2 - \rho} \geq 0 \tag{12}$$

In the case of a constant elasticity of substitution CES (iso-elastic case) demand, we have

$$p(q) = -\beta q^{-\frac{1}{\sigma}} \tag{13}$$

Where the following conditions are met:

$$\varepsilon_d = \sigma,\ \rho = \frac{\sigma + 1}{\sigma} > 1 \text{ and } e_d = \frac{1}{\rho - 1}$$

The exact pass-through rate mechanism (100%) is given as:

$$\frac{\partial \log p}{\partial \log c} = 1 \tag{14}$$

For the non CES demand function the pass-through rate mechanism is a function of elasticity and convexity conditions. Specifically, we have two distinct cases:

a) If the pass-through exceeds unity (more than 100%), the demand is characterised as "*superconvex*" since it holds $\rho > \frac{e_d + 1}{e_d}$ (15)

b) If the pass-through is less than unity (<100%), the demand can be characterised as "*subconvex*" since $\rho < \frac{e_d + 1}{e_d}$ (16)

According to Mrazova and Neary (2017), the demand functions implying constant proportional pass-through are given by the following formula:

$$p(q) = \frac{\beta}{q}\left(q^{\frac{k-1}{k}} + \gamma\right)^{\frac{k}{k-1}} \tag{17}$$

It holds that the constant proportional pass-through rate is simply given as:

$$\frac{\partial \log p}{\partial \log c} = k \tag{18}$$

Combining Eq. 10 and Eq. 17 we notice that $a \neq k$.

4. Data and Methodology

This section describes the data that we used in this study, while providing and analysing the necessary descriptive statistics for the sample variables. Moreover, we discuss and analyse the empirical framework and the econometric methodology applied to estimate the degree of carbon pass-through.

4.1 Variable description

In order to study the pass-through of emissions costs to wholesale electricity prices in the Greek electricity market over the period 2014-2017, we used different sources of data, concerning the wholesale electricity prices, the variable cost of thermal units per fuel type, the emissions cost and the temperature.

The prices of the European Emission Allowances (EUA) were derived from the European Energy Exchange (EEX) platform. The actual values of temperature were derived from the Meteologica SA platform, a global weather service provider, elaborating data from observed temperature values in Greece. The system marginal prices of the Greek day-ahead wholesale market has been derived from the public available data from the responsible institution, namely the Hellenic Market Operator (LAGIE), which recently transferred its relevant responsibilities to the mid-2018 established Hellenic Energy Exchange (HELEX), towards the adoption of the new market according to the European "*target model*".

The Greek interconnected power system in Greece consists of fourteen lignite and nine combined cycle (CCGT) natural gas power stations. Those units have their own techno-economic characteristics, which lead to different variable costs. The estimation of the variable cost of each unit over the examined period has been based on the published day-ahead scheduling by the Hellenic market Operator (LAGIE), considering that the marginal unit was the price setter. We have also considered the Ministerial decisions APEHL/C/F1/182348/24.08.2016 and APEHL/C/F1/178634/03.07.2017 concerning the costs of the lignite thermal units by the PPC, as well the cost of the public electronic auctions from the Public Gas Supplier (DEPA), which stands as the dominant gas supplier to electricity producers in Greece over the examined period.

Actual values for climate data such as temperature (in ^{o}C), wind speed (in Beaufort), humidity (in %) and solar radiation (in daily hours) have been provided by the Hellenic National Meteorological Service (EMY). Those data, which have been provided for 24 climate stations within the Greek territory, have been used to derive average national values. Actual values of temperature (in ^{o}C) have been also derived from the Meteologica SA platform. The latter constitutes a global weather service provider, elaborating data from observed temperature values in Greece.

The summary statistics of the sample variables are presented in the following table. As it is evident the data show significant variability in relation to the mean. Moreover, the sample variables do not follow the normal distribution since the mean is different from the estimated median of their Probability Density Function (PDF). In addition, the relative values of the skewness and kurtosis measures are not equal to zero and three respectively, indicating leptokurtic and platykurtic distributions (see Table 2).

<Insert Table 2 about here>

In order to get a clear picture about the pass-through rate mechanism we illustrate the evolution of prices (electricity and emissions prices) over the sample period. As it can be seen from Figure 2, wholesale electricity prices (e.g system marginal prices) depict a significant variation over the sample period. , besides the regulatory constraint not allowing bidding below the MAVC. This constraint offsets the possibility of very low or even negative prices, in contradiction with central European energy exchanges. However, this regulatory constraint does not affect the price formation towards high positive prices, leading to a considerable variation that can be attributed to external factors (shocks) generated by variations in the demand and supply conditions (Fabra and Reguant, 2014). Specifically, demand conditions include inter alia the level of economic activity and weather controls such as temperature variation and humidity. These factors, display a strong seasonal component since electricity demand varies during different seasons (e.g., winter-summer) and days within the week (e.g weekday-weekend). This volatility is fully reflected on the evolution of the SMP in Greece, where price hikes usually appeared in summer months (see July and August for the years 2014 and 2017) are followed by periods of prolonged price rigidity (autumn 2015 and 2016).

<Insert Figure 2 about here>

On the other hand, supply conditions include wind speed and sunshine in order to account for the substantial presence of wind power capacity and growing photovoltaic penetration in Greece respectively. Supply conditions usually vary with the availability of Renewable Energy Sources (RES) such as hydro and wind and are also correlated with changes in input prices, namely lignite, natural gas and crude oil price (see Fabra and Reguant, 2014). However, the reliability and quality of electricity supply is, vulnerable to non-stochastic variations (i.e shocks, disruptions) generated either from external factors, such as natural disasters (e.g., draughts, floods, earthquakes, hurricanes, etc), or human activity including inter alia power accidents, shut down of lignite mines (Apergis and Polemis, 2018). We must mention thought that such types of supply shocks were not reported during the sample period. Lastly, despite the fact that emissions costs depict a much smaller variation compared to SMPs, the level of wholesale electricity prices is being affected by the magnitude of the pass-through.

4.2 Empirical Framework

We begin our empirical modelling by considering the most common (baseline model) specifications employed by the pass-through rate literature (Goldberg and Campa, 2006; Nakamura and Zerom, 2010). The simplest of these is the Distributed Lag (DL) model, of the following form:

$$\Delta \log(SMP_{jt}) = a + \beta_j + \beta_s + \sum_{l=1}^{L} \gamma_l \Delta \log(EUA_{t-l}) + \varepsilon_{jt} \tag{19}$$

where $SMP_{j,t}$ is the wholesale price of electricity (i.e System Marginal Price) on each hour j at day t (common to all power plants). $\Delta SMP_{j,t}$ is the change in the wholesale electricity price from day t-1 to day t in hour j, EUA_t is the carbon emissions price at day t (common for every plant and every hour), ΔEUA_{t-l} is the change in the emissions price from day t-1 to day t, L is the number of lags in the emissions price, α is the intercept, β_j is a set of dummy variables, and β_s is a set of seasonal dummy variables. Finally, $\varepsilon_{i,t}$ are zero mean i.i.d. errors.

The coefficients γ_l denote the rate of change in wholesale electricity prices associated with a given percentage change in input cost (emissions costs) or simply the relevant short-run pass-through elasticities (Nakamura and Zerom, 2010). The sum of these elasticities simply denote the long-run pass-through elasticity. We have also estimated the baseline model in its linear form in order to compare and critically discuss our empirical findings with other similar studies.

We begin by estimating the baseline model with the use of the fixed effects (FE) estimator. In this way we allow a different intercept for every power plant. However, both FE and random effects (RE) estimators are inefficient in the presence of heteroskedasticity (Baltagi, 2002). To take into consideration heteroskedasticity and various patterns of correlation between residuals, an instrumental variable (IV) approach was taken into account. Moreover, in order to address concerns regarding endogeneity in some variables and improve the efficiency of our estimators, we use lagged levels as instruments of the endogenous variable (EUA_t) with standard errors robust to heteroskedasticity and within-cross section serial correlation. To assess instrument validity we report an Anderson LM statistic test under the null hypothesis that the model is underidentified (i.e. the matrix is not full column rank). Moreover, to test for weak instruments, we report Cragg-Donald Wald F statistics compared to their respective critical values.

Similarly to Fabra and Reguant (2014), we estimate the following model:

$$SMP_{jt} = a_0 + a_1 EUA_t + b_1 X_t^{COM} + b_2 X_t^{D} + b_3 X_t^{S} + \gamma_t + v_{jt} + \varepsilon_{jt} \tag{20}$$

where the dependent variable denotes the wholesale price of electricity SMP_{jt} on each hour j at day t. EUA_t denotes the emissions (carbon) price at day t (common to all hours across the power plants), $X_t^{COM} = \begin{bmatrix} COAL_t \\ GAS_t \\ BRENT_t \end{bmatrix}$ is a vector of exogenous (common) control variables denoting the commodity prices of lignite (COAL), natural gas (GAS) and crude oil (BRENT) respectively. $X_t^{D} = \begin{bmatrix} TEMP_t \\ HUM_t \end{bmatrix}$ also represents a demand vector of exogenous (common) control variables denoting weather conditions such as temperature (TEMP) and humidity (HUM) respectively, while $X_t^{S} = \begin{bmatrix} WIND_t \\ SUN_t \end{bmatrix}$ denotes the vector of exogenous (common) control variables capturing the effect of climatic variations such as wind speed (WIND) and sunshine (SUN) respectively.[1] The γ_t stands

[1] We must mention though that wind speed and an increased level of sunshine (measured by the number of days with sunshine) lead to a reduction in wholesale electricity prices due to the presence of substantial renewable power generation in Greece (i.e wind capacity, high level of sunshine, etc).

for the time fixed effects and v_i is a vector of fixed effects (i.e hour FE, month FE, temperature FE, etc) to control for differences across power plants (e.g differences in technology used in the production process, different level of efficiency between the thermal electricity units, different cost structure and fuel mix of the power plants) and for potential trends and fluctuations (i.e month of sample, day of the week and hour fixed effects). The inclusion of time fixed effects controls for changing technology and preferences over time since the last four years has been significant structural changes in the Greek electricity sector (e.g NOME auctions, abolishment of 30% rule, divestiture of two lignite power plants, etc). Finally ε_{it} is the idiosyncratic error term that is assumed to be i.i.d.

5. Results and discussion

This section presents the empirical findings of the study. We have used an unbalanced micro-level panel comprising of Greek power plants (N=23) spanning the period January 2014 to December 2017. For concreteness, we have divided this section into three distinct ones depicting and discussing the econometric results obtained by each relevant model (Baseline, IV model) along with the necessary robustness checks accounting for the use of different specifications (logged, non-linear, etc).

5.1 Baseline model

Table 3 presents the empirical findings of the wholesale electricity prices generated by two different DL models (log and levels specifications) estimated by OLS controlling for FE. As it is evident, the results indicate a substantial amount of incomplete pass-through rate expressed in percentage terms.

Specifically, for the logged model (see Column 1), the estimated long-run pass-through (elasticity) is statistically significant and equal to 0.475. This means that a 10% increase (decrease) in carbon emissions price (i.e commodity cost) eventually will lead to only about a half (4.7%) of a percentage increase (decrease) in wholesale electricity prices. Similar findings hold for the levels specification DL model (see Column 2) since the long-run pass through coefficient is estimated to 0.433. This finding, reveals that a one euro increase (decrease) in emissions costs translates, on average, into a fourty-three cents increase (decrease) in electricity prices.

Table 3 also portrays that there is a substantial delay in the response of wholesale prices to carbon costs since for logged prices more than half of the adjustment to a change in costs occurs seven periods after the initial cost shock. However, the opposite is evident when we account for a different DL model specification (levels). In such a case, the price adjustment mechanism is more direct. Lastly, similar to Nakamura and Zerom, (2010) we do not find evidence that prices respond asymmetrically to input cost variations (e.g carbon prices).

<Insert Table 3 about here>

5.2 Instrumental variable model

Estimating Equation (19) with OLS can be problematic because wholesale electricity prices can be endogenously affect the level of carbon emissions prices. This may happen either for macroeconomic (i.e common trends across the EU electricity markets) or microeconomic reasons (e.g general equilibrium effects of emissions prices on fuel cost and the electricity demanded by other sectors) as suggested by other researchers (Duso and Szücs, 2017; Fabra and Requant, 2014). To address this concern of reverse causality, we adopt the instrumental variable (IV) approach and the 2SLS, which is applied in other studies as well (Chen et al, 2018; Loy et al, 2016; Dai et al, 2014; Fabra and Requant, 2014; Lewbel, 2012).

Table 4 summarizes the estimates of Equation (20) using the IV approach. The specifications include year, month, and hour FE, demand and supply controls (e.g temperature, humidity, wind speed, sunshine) as well as other common controls (e.g commodity prices of oil, gas and coal). Robust standard errors are reported in parentheses. Column (1) reports the baseline estimates with only common FE present. The coefficient of interest is that of carbon emissions price (EUA) and is estimated to 1.081. This means that a 10% increase (decrease) of emissions costs will lead to a slightly larger (10.8%) increase (decrease) in wholesale electricity prices, indicating an almost complete pass-through. This could be attributed either to markup adjustment by the power companies in tandem with the small magnitude of own price elasticity of demand, or to the absence of relevant price rigidities (Fabra and Reguant, 2014). All the remaining variables have the anticipated signs and are statistically significant.

As it is evident, higher (lower) wind speed (WIND) is robustly correlated with lower (higher) wholesale electricity prices, as a one per cent increase of wind speed is associated with a decrease in the level of system marginal price of about 88%. This finding, which is in alignment with the study of Fabra and Reqant (2014) may be attributed to the existence of significant wind capacity in Greece, which causes the industry supply curve to shift to the right, decreasing the level of SMP. Similarly, we find that temperature (TEMP) is negatively correlated with electricity prices indicating that a 10% increase (decrease) in the temperature level will reduce (increase) the system marginal price by about 3% on average. This is consistent with electricity demand being higher during winter and in very hot summer days (Fabra and Requant, 2014). It is worth mentioning that the rest weather covariates (SUN and HUM) are also negatively correlated with the wholesale electricity prices. Their estimated coefficients range from -0.0550 to -0.240 respectively. We must stress though that the negative sing of the sunshine level can also be attributed to the excess supply of photovoltaic capacity in Greece. From the commodities included in the estimation (COAL, GAS and BRENT), only coal prices are negatively correlated with electricity prices (-0.0353). On the contrary, natural gas (GAS) and oil prices (BRENT) are positively correlated with the level of system marginal price (SMP) pointing that some aggregate macroeconomic effects are present.

<Insert Table 4 about here>

Similarly to Fabra and Requant (2014), we include some other specifications (see Columns 2-5) in order to introduce the effect of several additional controls to the baseline specification (e.g Column 1). As it is evident, all the pass-through estimates are statistically significant and robust across specifications, with their magnitude ranging from 0.637 to 1.112. It is important to note that, when we allow for the effect of temperature to have a different impact on price depending on the month of the year (see Column 2), the pass-through estimate is substantially lower compared to the rest specifications, revealing that in this case the pass-through is incomplete.[2] On the other hand, when both sets of control are present (see Column 3), the pass-through coefficient is estimated to 1.112, indicating that a 10% increase (decrease) of carbon price leads to a greater increase (decrease) by about 11.1% in wholesale electricity prices. These results provide further evidence that the pass-through in the electricity market is very high, particularly in those hours in which we would expect firms to price marginally.

Lastly, several precautions are taken in order to avoid the problem of instrument proliferation. Tests reported in the bottom of Table 4 clearly show that our instruments are exogenous and they do not suffer from weak identification problem (Cragg-Donald Wald F statistic). Further, the instrumental variable technique is necessary while our model is not under-identified (Anderson LM statistic) since in all of the specifications the null hypothesis is rejected. Taken together, we argue that the model is properly identified.

5.3 Robustness checks: A logged linear approach

In this part of the analysis we have performed several checks to sharpen the robustness of our results. Firstly, we attempt to conceptualize the pass-through rate mechanism by estimating the

[2] This can be important, as a relatively warm day tends to reduce electricity consumption during the winter, but to increase it during the summer (Fabra and Requant, 2014).

econometric model in a logged-linear way. In this way we will try to directly estimate the relevant elasticities in order to check their magnitudes compared with the estimated coefficients drawn from the linear specifications. The new results are reported in Table 5 and they signify important similarities to those reported in Table 4. The variables included in the logged-linear model (see Columns 1-5) retain not only their expected theoretical signs but also their statistical significance. However, they turn out to be larger in most of the specifications and they do not suffer from downward bias and endogeneity.

As it is evident the pass-through rate elasticity ranges from 0.639 to 1.196 (see Columns 2 and 1 respectively). Moreover, all the weather demand and supply controls have the expected (negative) signs and are statistically significant, stressing the significance of RES penetration in the electricity price formulation. This finding incurs some important policy implications regarding the efficient use of electricity in the Greek energy balance. The commodity prices seem to statistically significant impact the SMP but in a non-uniform way. The basic model (see Column 1) indicates that coal price elasticity is negatively correlated with the electricity prices (-0.0584), while the effect of the rest commodity prices (GAS and BRENT) is positive (0.0355 and 0.135 respectively). On the contrary, when we control for the presence of specific FE (i.e hour, temperature, month, etc), these results are reversed. Specifically, the impact of coal price on electricity price formulation is positive in all of the rest specifications (see Columns 2-5) with the estimated price elasticities within a close range (from 0.705 to 0.882). Moreover, the effect of oil turns to negative with the estimated elasticities varying within a broader range (-0.0322 to -0.221).

<Insert Table 5 about here>

5.4 Robustness checks: A non-linear approach

Within the last years, there is a growing strand of literature supporting the argument that input cost transmission mechanism follows a non-monotonic distribution (see among others Polemis and

Tsionas, 2017; Polemis and Tsionas, 2016; Loy et al, 2016). According to this literature, the employment of a linear (monotonic) methodological framework is not able to capture the exact form of the price pass-through relationship. In such a case, the cost pass-through processes exhibit a non-linear behavior which is usually modeled by a threshold-error-correction-mechanism (Loy et al, 2016).

Following the above discussion posed by the relevant references, this part of the study, employs a simple quadratic approximation of Equation (20). Table 6 presents the empirical findings drawn from the non-linear specifications. As it is evident, all the coefficients are statistically significant and come with the expected sign, indicating strong non-linear effects. The price-pass through rate coefficient exceeds unity in all of the specifications (see Columns 1-4), ranging from 1.054 to 1.091, implying that a 10% increase (decrease) in emissions costs translates, on average, into an increase (decrease) in wholesale electricity prices of 10.67% approximately.

<Insert Table 6 about here>

6. Concluding remarks and policy implications

This study employed both a linear and a non-linear panel cointegration modelling approach to shed light to the carbon price pass-through mechanism between wholesale electricity prices and a set of demand and supply covariates for an expanded set of 23 power plants in Greece. The (logged) linear parameter models document that the emissions cost estimates are on average greater than one, implying an almost complete price pass-through in the Greek electricity industry. Moreover, the non-linear parameter estimates confirm the above finding.

It is worth mentioning that our results receive empirical support from those reported by Fabra and Requant (2014) in the case of the Spanish electricity industry since both studies argue that the carbon price pass-through is almost complete. However, the empirical findings of this study are different from those reported in the earlier literature on price-pass through (see Duso and Szücs, 2017, Goldberg and Hellerstein, 2013; Nakamura and Zerom, 2010), highlighting that an incomplete pass-through of carbon costs to wholesale electricity prices is the usual case rather than the exception in the pass-through nexus. The presence of homogeneity in the results could partly explain the findings due to the absence of variation across power plants. The findings remained robust under different econometric specifications.

Our results have important policy implications. As of January 2013 the ETS is in its third and more mature phase (2013-2020) since a single, EU-wide cap on carbon emissions applies in the electricity industry in place of the previous system of national caps between the EU member states. Within this period, auctioning is the default method for allocating allowances (instead of grandfathering or free allocation of permits), and harmonised allocation rules apply to the allowances still given away for free.

The finding of an almost complete carbon price pass-through suggests that the emissions cost is fully shifted on the consumers (i.e power suppliers), which in turn may be internalized by them across the vertical chain of electricity industry. As a consequence, we argue that the compulsory auctioning of tradable permits during the third period of the ETS might not trigger an inflationary effect on electricity prices, at least in the short run. This raises important equity implications and distributional effects generated by possible market interventions (i.e taxation of profits).

Another important issue is that the negative correlation between weather covariates with the SMP calls for further market design by policy makers and practitioners toward a more efficient energy conservation scheme. As a result, financing RES penetration could be an important driver to stimulate "*green*" investments in Greece in order to achieve specific macroeconomic (i.e debt financing, sustainable growth, emissions reduction, etc) as well as microeconomic goals (i.e competitive electricity prices, consumer welfare, etc). However, a more thorough research is needed to reach solid conclusions in relevance to the above considerations.

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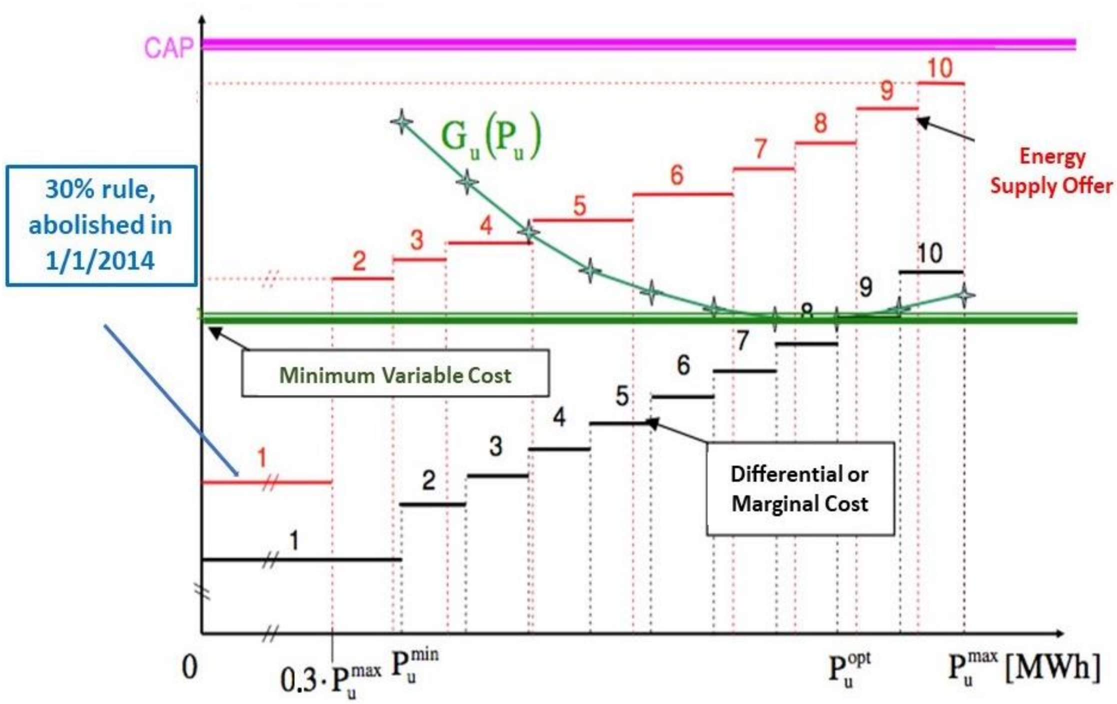
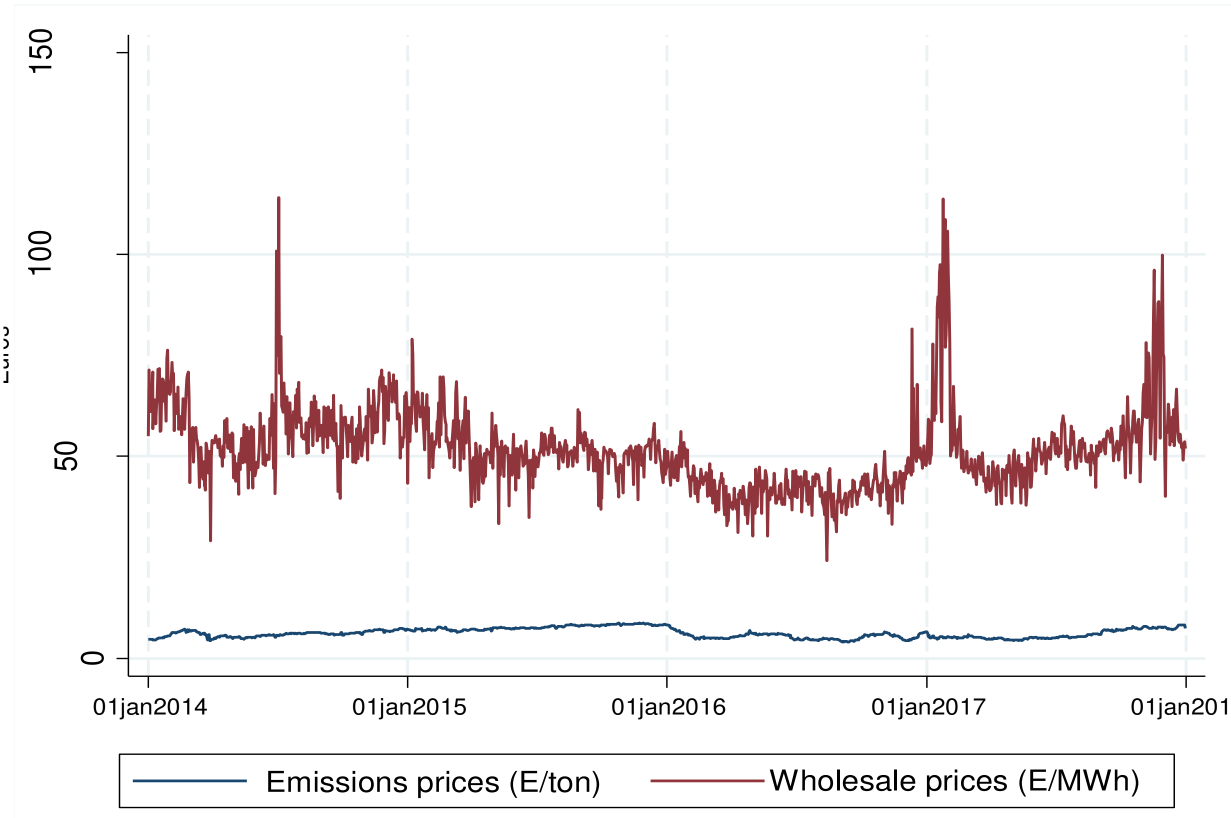
Figures and Tables

Figure 1: Graphical illustration of the Greek wholesale electricity market



Notes: The red curve denotes the energy supply offer of a thermal power plant. The black curve represents the Differential cost of a thermal power plant, while the green curve denotes its minimum variable cost, for different power outputs, among unit's technical minimum (P_{min}) and technical maximum (P_{max})

Figure 2: Evolution of EUA and wholesale electricity prices (Jan 2014-Dec 2017)



Source: European Energy Exchange (EEX) platform and Hellenic Market Operator (LAGIE).

Table 1: Industry characteristics of the four largest power generators in Greece

Characteristics	**PPC**	**IPP1**	**IPP2**	**IPP3**
Total number of thermal units	18	2	2	2
Average emissions rate (tCO_2/MWh)	1.24	0.4	0.4	0.5
Average thermal capacity (MW)	5,745	866	800	569
Average lignite capacity share (%)	68.09	0.0	0.0	0.0
Average CCGT capacity share (%)	31.91	100.0	100.0	74.17
Average oil/gas capacity share (%)	31.91	100.0	100.0	100.0

Source: LAGIE

Notes: PPC, denotes the Public Power Corporation, IPP stands for the Independent Power Producer. The sample period covers January 2014 to December 2017, including all thermal units in the Greek wholesale electricity industry that are active. The average measures are based on hourly values during the sample period.

Table 2: Summary statistics

Variables	**Observations**	**Mean**	**Median**	**Min**	**Max**	**Standard deviation**	**Skewness**	**Kurtosis**
SMP	804,860	51.71	49.98	0	299	14.31	2.656	22.42
EUA	804,860	6.217	6.040	0	8.680	1.206	0.265	1.917
COAL	793,820	50.36	52.67	33.77	66.08	9.170	-0.154	1.813
GAS	804,860	3.114	2.920	1.490	8.150	0.884	1.234	6.039
BRENT	804,860	62.09	53.98	0	115.2	23.62	1.031	2.847
TEMP	675,554	16.7	16.3	-3.9	38.8	7.6	0.078	2.284
WIND	804,860	6.363	6.063	1.959	17.24	2.164	0.886	4.241
HUM	804,860	66.74	66.57	39.85	88.29	9.634	-0.0443	2.154
SUN	804,860	7.397	7.900	0	13.90	4.244	-0.384	1.939

Notes: SMP stands for the wholesale electricity price measured in euro/MWh, EUA denotes the carbon emissions price expressed in euro/tone, COAL denotes the NYMEX coal futures near-month contract final settlement price expressed in USD dollars per tone, GAS is the natural gas spot price expressed in USD dollars per Million Btu, BRENT denotes the Brent spot price FOB measured in USD dollars per Barrel, TEMP stands for the average daily temperature measured in Celsius degrees (^oC), WIND represents the average daily wind speed expressed in Beaufort scale, HUM stands for the average daily humidity rate (%) and finally SUN is the average daily solar radiation (sunshine) measured in daily hours. The sample period covers January 2014 to December 2017.

Table 3: Pass-through regression results (Baseline model)

Variable	**(1)** **logged specification**	**(2)** **levels specification**
Δ Emissions price (t)	-0.0625*	0.624**
	(0.0337)	(0.280)
Δ Emissions price (t-1)	0.0448	-1.019***
	(0.0337)	(0.280)
Δ Emissions price (t-2)	-0.0428	-2.469***
	(0.0337)	(0.281)
Δ Emissions price (t-3)	0.153***	-0.176
	(0.0337)	(0.281)
Δ Emissions price (t-4)	0.0573*	0.364
	(0.0337)	(0.281)
Δ Emissions price (t-5)	-0.0351	0.185
	(0.0337)	(0.281)
Δ Emissions price (t-6)	-0.0160	0.426
	(0.0337)	(0.281)
Δ Emissions price (t-7)	0.205***	2.498***
	(0.0337)	(0.281)
Δ Emissions price (t-8)	0.171***	-
	(0.0337)	
Long run pass-through	**0.475***	**0.433***
	(0.0236)	**(0.0396)**
Observations	802,804	804,852
F-test	10.47***	22.96***
	[0.000]	[0.000]

Notes: The sample period covers January 2014 to December 2017. The number of lags has been selected by using the AIC in such a way that adding extra lags will not change the magnitude of the estimated long-run pass-through coefficient. The numbers in square brackets denote P-values. Clustered standard errors in parentheses. *** p<0.01.

Table 4: IV pass-through regression results (linear model)

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
EUA	**1.081*****	**0.637*****	**1.112*****	**1.054*****	**1.082*****
	(0.0203)	(0.0214)	(0.0263)	(0.0263)	(0.0269)
WIND	-0.880***	-0.759***	-0.826***	-0.805***	-0.834***
	(0.00831)	(0.00823)	(0.00889)	(0.00805)	(0.00827)
SUN	-0.240***	-0.262***	-0.295***	-0.183***	-0.192***
	(0.00580)	(0.00564)	(0.00610)	(0.00557)	(0.00566)
TEMP	-0.298***	0.206***	0.746***	-0.0616***	0.557***
	(0.00548)	(0.00407)	(0.0132)	(0.00530)	(0.0128)
HUM	-0.0550***	-0.0753***	-0.135***	-0.0852***	-0.0697***
	(0.00281)	(0.00275)	(0.00323)	(0.00274)	(0.00310)
COAL	-0.0353***	1.331***	1.269***	1.129***	1.178***
	(0.00487)	(0.00830)	(0.00934)	(0.00852)	(0.00863)
GAS	1.735***	1.411***	1.438***	1.533***	1.846***
	(0.0547)	(0.0876)	(0.0956)	(0.0880)	(0.0893)
BRENT	0.103***	-0.223***	-0.0937***	-0.0646***	-0.00397
	(0.00252)	(0.00293)	(0.00392)	(0.00344)	(0.00377)
		Diagnostics			
Observations	669,482	669,482	669,482	669,482	669,482
R-squared	0.236	0.282	0.182	0.312	0.312
F-test	7,450.57***	7,545.96***	5,332.35***	1,498.76***	1,471.54***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Anderson LM statistic	1.3e+04***	1.2e+04***	8,787.748***	7,388.289***	7,124.139***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Cragg-Donald Wald F statistic	1.4e+04***	1.2e+04***	8,903.945***	7,467.446***	7,197.475***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
		Fixed Effects (FE)			
Base FE	YES	YES	YES	YES	YES
Month X Year FE	NO	YES	YES	YES	YES
Month X Temp FE	NO	NO	YES	NO	YES
Month X Hour FE	NO	NO	NO	YES	YES

Notes: SMP stands for the wholesale electricity price measured in euro/MWh, EUA denotes the carbon emissions price expressed in euro/tone, COAL denotes the NYMEX coal futures near-month contract final settlement price expressed in USD dollars per tone, GAS is the natural gas spot price expressed in USD dollars per Million Btu, BRENT denotes the Brent spot price FOB measured in USD dollars per Barrel, TEMP stands for the average daily temperature measured in Celsius degrees (ºC), WIND represents the average daily wind speed expressed in Beaufort scale, HUM stands for the average daily humidity rate (%) and finally SUN is the average daily solar radiation (sunshine) measured in daily hours. The sample period covers January 2014 to December 2017. Anderson LM statistic and Cragg-Donald Wald F statistic denote the under identification and weak identification tests respectively where rejection of the null hypothesis indicates that the model is properly identified. The numbers in square brackets denote P-values. Standard errors in parentheses. *** $p<0.01$.

Table 5: IV pass-through regression results (log-linear model)

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(EUA)	**1.196*****	**0.639****	**1.146*****	**1.137*****	**1.139*****
	(0.0183)	(0.0249)	(0.0289)	(0.0279)	(0.0280)
log(WIND)	-0.0646***	-0.0590***	-0.0583***	-0.0595***	-0.0590***
	(0.000512)	(0.000488)	(0.000495)	(0.000439)	(0.000454)
log(SUN)	-0.0235***	-0.0223***	-0.0215***	-0.0173***	-0.0160***
	(0.000406)	(0.000380)	(0.000386)	(0.000348)	(0.000350)
log(TEMP)	-0.0124***	0.00754***	0.000954**	-0.00693***	0.00346***
	(0.000436)	(0.000367)	(0.000487)	(0.000373)	(0.000456)
log(HUM)	-0.141***	-0.168***	-0.158***	-0.151***	-0.103***
	(0.00352)	(0.00322)	(0.00352)	(0.00298)	(0.00332)
log(COAL)	-0.0584***	0.882***	0.861***	0.705***	0.716***
	(0.00434)	(0.00823)	(0.00891)	(0.00796)	(0.00810)
log(GAS)	0.0355***	0.0470***	0.0226***	0.0491***	0.0361***
	(0.00304)	(0.00473)	(0.00481)	(0.00435)	(0.00439)
log(BRENT)	0.135***	-0.216***	-0.221***	-0.0645***	-0.0322***
	(0.00296)	(0.00409)	(0.00503)	(0.00435)	(0.00467)
		Diagnostics			
Observations	618,712	618,712	618,712	618,712	618,712
R-squared	0.190	0.306	0.309	0.435	0.439
F-test	6,358.51***	6685.071***	5,367.47***	1,621.94***	1,593.55***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Anderson LM statistic	1.6e+04***	7,885.542***	5,896.517***	5,181.641***	5,118.718***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Cragg-Donald Wald F statistic	1.7e+04***	7,986.816***	5,952.755***	5,222.914***	5,158.869***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
		Fixed Effects (FE)			
Base FE	YES	YES	YES	YES	YES
Month X Year FE	NO	YES	YES	YES	YES
Month X Temp FE	NO	NO	YES	NO	YES
Month X Hour FE	NO	NO	NO	YES	YES

Notes: SMP stands for the wholesale electricity price measured in euro/MWh, EUA denotes the carbon emissions price expressed in euro/tone, COAL denotes the NYMEX coal futures near-month contract final settlement price expressed in USD dollars per tone, GAS is the natural gas spot price expressed in USD dollars per Million Btu, BRENT denotes the Brent spot price FOB measured in USD dollars per Barrel, TEMP stands for the average daily temperature measured in Celsius degrees (°C), WIND represents the average daily wind speed expressed in Beaufort scale, HUM stands for the average daily humidity rate (%) and finally SUN is the average daily solar radiation (sunshine) measured in daily hours. The sample period covers January 2014 to December 2017. Anderson LM statistic and Cragg-Donald Wald F statistic denote the under identification and weak identification tests respectively where rejection of the null hypothesis indicates that the model is properly identified. The numbers in square brackets denote P-values. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$.

Table 6: IV pass-through regression results (non-linear model)

Variable	**(1)**	**(2)**	**(3)**	**(4)**
EUA	**1.092*****	**1.058*****	**1.065*****	**1.054*****
	(0.00643)	(0.00639)	(0.0124)	(0.00709)
WIND	-0.629***	-0.626***	-0.215***	-0.655***
	(0.00879)	(0.00868)	(0.0379)	(0.0336)
SUN	-0.285***	-0.214***	-0.212***	-0.215***
	(0.00616)	(0.00612)	(0.00685)	(0.00616)
TEMP	-0.0542***	-0.970***	-0.774***	-0.978***
	(0.00305)	(0.00952)	(0.0112)	(0.00955)
HUM	-0.0508***	0.0420***	-0.0206***	0.0415***
	(0.00280)	(0.00292)	(0.00344)	(0.00294)
COAL	-2.960***	-2.826***	-3.846***	-2.780***
	(0.0326)	(0.0323)	(0.0400)	(0.0326)
GAS	2.175***	-0.653**	-6.953***	-1.191***
	(0.295)	(0.292)	(0.345)	(0.294)
BRENT	0.191***	0.257***	0.200***	0.302***
	(0.00680)	(0.00675)	(0.00762)	(0.00733)
$WIND^2$	-	-	-0.0270***	-0.108***
			(0.00249)	(0.0258)
WIND X Trend	-	-	-	5.31e-06***
				(1.26e-06)
$TEMP^2$	-	0.0280***	0.0244***	0.0282***
		(0.000274)	(0.000313)	(0.000275)
$COAL^2$	0.0328***	0.0314***	0.0424***	0.0309***
	(0.000323)	(0.000320)	(0.000402)	(0.000325)
GAS^2	0.761***	1.042***	2.342***	1.119***
	(0.0506)	(0.0500)	(0.0602)	(0.0503)
$BRENT^2$	-0.00308***	-0.00320***	-0.00411***	-0.00349***
	(5.66e-05)	(5.58e-05)	(6.44e-05)	(5.96e-05)
Base FE	YES	YES	YES	YES
		Diagnostics		
Observations	669,482	669,482	669,482	665,202
R-squared	0.088	0.111	0.115	0.1138
F-test	13,524.10***	13,908.07***	9,960.60	11,977.03***
	[0.000]	[0.000]	[0.000]	[0.000]
Anderson LM statistic	1.2e+05***	1.2e+05***	4.0e+04***	1.0e+05***
	[0.000]	[0.000]	[0.000]	[0.000]
Cragg-Donald Wald F statistic	1.5e+05***	1.5e+05***	4.2e+04***	1.2e+05***
	[0.000]	[0.000]	[0.000]	[0.000]

Notes: SMP stands for the wholesale electricity price measured in euro/MWh, EUA denotes the carbon emissions price expressed in euro/tone, COAL denotes the NYMEX coal futures near-month contract final settlement price expressed in USD dollars per tonne, GAS is the natural gas spot price expressed in USD dollars per Million Btu, BRENT denotes the Brent spot price FOB measured in USD dollars per Barrel, TEMP stands for the average daily temperature measured in Celsius degrees (^{o}C), WIND represents the average daily wind speed expressed in Beaufort scale, HUM stands for the average daily humidity rate (%) and finally SUN is the average daily solar radiation (sunshine) measured in daily hours. Trend denotes a linear time trend to capture technological spillovers. The sample period covers January 2014 to December 2017. Anderson LM statistic and Cragg-Donald Wald F statistic denote the under identification and weak identification tests respectively where rejection of the null hypothesis indicates that the model is properly identified. The numbers in square brackets denote P-values. Standard errors in parentheses. *** $p<0.01$.